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Marco Antonio Cotrina-Teatino

mcotrinat@unitru.edu.pe

National University of Trujillo <https://orcid.org/0000-0003-3801-0370>

Jairo Jhonatan Marquina-Araujo

National University of Trujillo

José Néstor Mamani-Quispe

Universidad Nacional del Altiplano

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Dynamic mapping of flood susceptibility and exposure associated with the El Niño phenomenon using machine learning and geospatial modeling in Trujillo, Peru

Marco A. Cotrina-Teatino^{1,2,3*}, Jairo J. Marquina-Araujo^{1,2,3}, José N. Mamani-Quispe⁴

¹ Department of Mining Engineering, Faculty of Engineering, National University of Trujillo, Trujillo, 13001, Peru.

² Laboratory for Mine Design and Planning-DIPLAMIN, National University of Trujillo, Trujillo, 13001, Peru.

³ Research group in Advanced Modeling in Mining (GAMM), National University of Trujillo, Trujillo, 13001, Peru.

⁴ Department of Chemical Engineering, Faculty of Engineering, National University of Altiplano of Puno, Puno, 21001, Peru.

Corresponding author: Marco A. Cotrina-Teatino (mcotrinat@unitru.edu.pe)

Abstract

Flooding associated with El Niño recurrently affects Trujillo, Peru; however, conventional susceptibility maps are often static and do not represent how the response of the territory changes under new precipitation conditions or where these areas overlap with population and infrastructure. Therefore, the objective was to develop a dynamic geospatial framework for estimating flood susceptibility and exposure. Areas affected during the 2017, 2023, and 2025 events were reconstructed using Sentinel-1 imagery, and topographic, hydrological, geological, and meteorological variables were integrated. Random Forest, XGBoost, SVM, and ANN-MLP were compared using stratified cross-validation and an independent test set. Random Forest achieved the best performance, with a ROC-AUC of 0.9166, compared with 0.9099 for XGBoost, 0.8611 for ANN-MLP, and 0.8065 for SVM, and achieved AP = 0.9116, accuracy = 0.8371, and F1-score = 0.8393. SHAP identified terrain aspect, precipitation, elevation, and slope as the most influential factors in susceptibility. In 2017, the high and very high classes accounted for 52.95% of the exposed population; in the update of 14 September 2026, moderate susceptibility predominated, covering 57.17% of the modeled territory and 81.10% of the exposed population, while the high and very high classes accounted for 17.81%. It is concluded that the proposed approach enables susceptibility to be updated using GPM-IMERG without retraining the model and supports the preventive identification of priority areas.

Keywords: flood susceptibility; dynamic mapping; machine learning; Sentinel-1; GPM-IMERG.

1. Introduction

Floods are among the natural hazards with the greatest human impact, both because of their spatial extent and the increasing occupation of flood-prone areas. Between 2000 and 2018, 913 major events covered approximately 2.23 million km² and directly affected between 255 and 290 million people across different regions of the world. During this period, the population living in areas where flooding was observed increased by 20–24%, indicating that exposure continues to grow alongside the expansion of human settlements (Tellman et al. 2021). Currently, approximately 1.81 billion people, equivalent to nearly 23% of the global population, live in areas exposed to significant flood levels (Rentschler et al. 2022). This growth in population and built-up areas within susceptible zones increases the need to spatially identify where the greatest impacts may occur and which elements are exposed (Ehrlich et al. 2018; Mohanty and Simonovic 2021; Abedin et al. 2024).

Along the Peruvian coast, this issue is closely related to tropical Pacific variability, which can exceptionally alter the rainfall regime of a predominantly arid territory (Garreaud 2018; Peng et al. 2019). The 2017 Coastal El Niño demonstrated the magnitude of this phenomenon, when intense ocean warming off the Peruvian coast favored extraordinary rainfall and widespread flooding across the northern coast (Garreaud 2018; Peng et al. 2019). In Trujillo, these rains activated ravines such as San Ildefonso and generated flows that reached urbanized areas, highlighting the city's exposure to extreme hydrometeorological events (Guerrero Padilla et al. 2021). New episodes of intense rainfall affected the province during Cyclone Yaku in March 2023 and again caused flooding and debris flows in seven districts on 29 March 2025 (SENAMHI 2023; INDECI 2025a). Although the 2017, 2023, and 2025 events occurred under different meteorological conditions, their recurrence shows that Trujillo remains persistently exposed to rainfall episodes capable of generating substantial impacts on urbanized areas.

In the context of such events, accurately determining where flooding occurred is essential for identifying areas that tend to be affected and understanding their spatial distribution across the territory (Schumann and Moller 2015). Optical imagery has been widely used for this purpose, although its availability may be limited by cloud cover during periods of intense rainfall (Bentivoglio et al. 2022). Radar imagery provides a particularly useful alternative because it enables surface observation both during the day and at night and under adverse weather conditions (Twele et al. 2016; Li et al. 2018). In particular, Sentinel-1 has enabled the identification of flood-related changes by comparing images acquired before and after an event, facilitating the delineation of affected areas even when direct observation is limited (Cian et al. 2018). This capability has promoted its use for reconstructing historical events and generating spatial information that can subsequently be used to identify areas with a greater propensity for flooding (Mohammadi et al. 2020; Al-Ruzouq et al. 2024).

The identification of these areas has also advanced through the combined use of topographic, hydrological, geological, and environmental information. Factors such as elevation, slope, proximity to drainage channels, flow accumulation, soil moisture, and precipitation influence how water concentrates and moves across the surface (Tehrany et al. 2014; Rahmati et al. 2016). Machine learning makes it possible to relate these conditions to previously affected locations and to recognize patterns that may be difficult to represent through simple relationships (Mosavi et al. 2018; Demissie et al. 2024). Different applications have shown

favorable results with models such as Random Forest, Support Vector Machine, and XGBoost for delineating areas with different levels of flood susceptibility (Feizbahr et al. 2025). In northern Peru, Badillo-Rivera et al. (2025) combined Sentinel-1 imagery and machine learning to assess susceptibility associated with the 2017 Coastal El Niño in the Piura River basin, demonstrating the potential of integrating satellite information and terrain variables in this context.

However, adequately representing susceptibility requires considering that floods do not always occur under the same conditions. A model developed from a single episode may more strongly reflect the particular characteristics of that event, whereas incorporating observations from different situations allows a broader range of territorial responses to be represented (Portalés-Julià et al. 2025; Huang et al. 2026). It is also important to identify which factors are associated with areas classified as more susceptible, because an accurate prediction is more useful when it can be interpreted consistently with the physical conditions of the area (Lundberg and Lee 2017; Pradhan et al. 2023). For this reason, recent approaches seek not only to improve classification performance, but also to understand the influence of topography, drainage, precipitation, and other environmental characteristics on the resulting predictions (Pradhan et al. 2023; Badillo-Rivera et al. 2025).

Despite these advances, a large proportion of susceptibility maps continue to represent relatively permanent territorial conditions and therefore remain virtually unchanged after their development. This representation is useful for identifying areas that are naturally prone to flooding, but it does not fully reflect the fact that the probability of impact may change as precipitation increases or decreases (Mosaffa and Brocca 2024; Huang et al. 2026). In response to this limitation, approaches have begun to emerge that combine terrain predisposition with variable meteorological information to represent how susceptibility may change between different times or events (Mosaffa and Brocca 2024; Alcântara and Mantovani 2026). The availability of satellite precipitation products such as GPM-IMERG, with broad coverage and frequent updates, provides an opportunity to incorporate these variations and move toward maps that can be updated as recent rainfall conditions change (Huffman et al. 2020).

Susceptibility alone does not provide information on the significance of potential impacts, because their consequences also depend on the presence of people and the degree of territorial occupation. Population density and built-up area allow these two dimensions to be represented spatially and have been used to quantify exposure to floods and other natural hazards (Ehrlich et al. 2018; Mohanty and Simonovic 2021). Global products such as the Global Human Settlement Layer provide consistent information on population and built-up areas, facilitating their integration with flood and susceptibility maps (Ehrlich et al. 2018). This combination makes it possible to distinguish areas with similar physical conditions but different potential consequences due to the concentration of population and built-up elements (Tellman et al. 2021).

Despite the advances achieved, several components required to understand flooding are still commonly addressed separately. Satellite information has improved the identification of affected areas, and the diversity of observations has proven important for obtaining models that are more robust across different events (Portalés-Julià et al. 2025). At the same time, much of susceptibility mapping continues to primarily represent relatively stable territorial conditions, whereas recent approaches demonstrate the usefulness of incorporating precipitation as a variable factor that modifies the response between events (Alcântara and

Mantovani 2026). Population and built-up area, in turn, are often incorporated subsequently to estimate exposure, but they are not always part of a framework that connects historical observations, susceptibility, and updatable meteorological conditions (Rentschler et al. 2022). This separation highlights the need to integrate these dimensions within a common framework that takes advantage of multiple observed events and enables the representation of both territorial predisposition and its changes in response to recent precipitation.

In this context, the problem addressed in this research is that conventional maps make it possible to identify areas prone to flooding but provide a limited representation when precipitation conditions change and, by themselves, do not show where this susceptibility coincides with a greater presence of population and built-up areas. Therefore, the objective is to develop a dynamic geospatial framework for estimating flood susceptibility and exposure in the province of Trujillo through the integration of observations from the 2017, 2023, and 2025 events, satellite and geospatial information, and machine-learning models. The main novelty lies in learning the territorial response from multiple events, interpreting the factors associated with susceptibility, and subsequently updating its estimates using recent GPM-IMERG precipitation, while also incorporating population and built-up area to represent exposure. In this way, the study seeks to move from an essentially static map toward an updatable representation of susceptibility conditions and potentially exposed elements.

The article is organized into five sections. Following this introduction, Section 2 describes the study area, data, and methodology; Section 3 presents the results; Section 4 discusses the main findings and their limitations; and Section 5 summarizes the conclusions of the study.

2. Materials and methods

2.1. Study area

The study area comprises the province of Trujillo, located in the western sector of the department of La Libertad, on the northern coast of Peru (Fig. 1a). It covers an area of approximately 1,768.65 km² and includes urban areas, agricultural lands in the Moche River valley, and rural sectors along the Andean foothills. The territory exhibits a marked contrast between the plains near the Pacific Ocean, where much of the metropolitan area is located, and the higher-relief terrain farther inland, particularly in the districts of Simbal and Poroto (Fig. 1b) (MPT 2016).

The surroundings of the city are predominantly composed of Quaternary alluvial, fluvial, and aeolian deposits consisting of gravel, sand, silt, and clay. Accumulations of materials transported by ancient flows are also present within the ravines, whereas intrusive, sedimentary, and volcano-sedimentary rocks crop out in the surrounding hills. The main geomorphological units include alluvial plains, fluvial terraces, flood-prone surfaces, piedmont areas, hills, and mountains. The low-lying surfaces of the Moche Valley and the deposits located at the outlets of the ravines are particularly relevant for understanding the distribution of flood-susceptible areas and the movement of water and sediments toward urbanized zones (Medina et al. 2017).

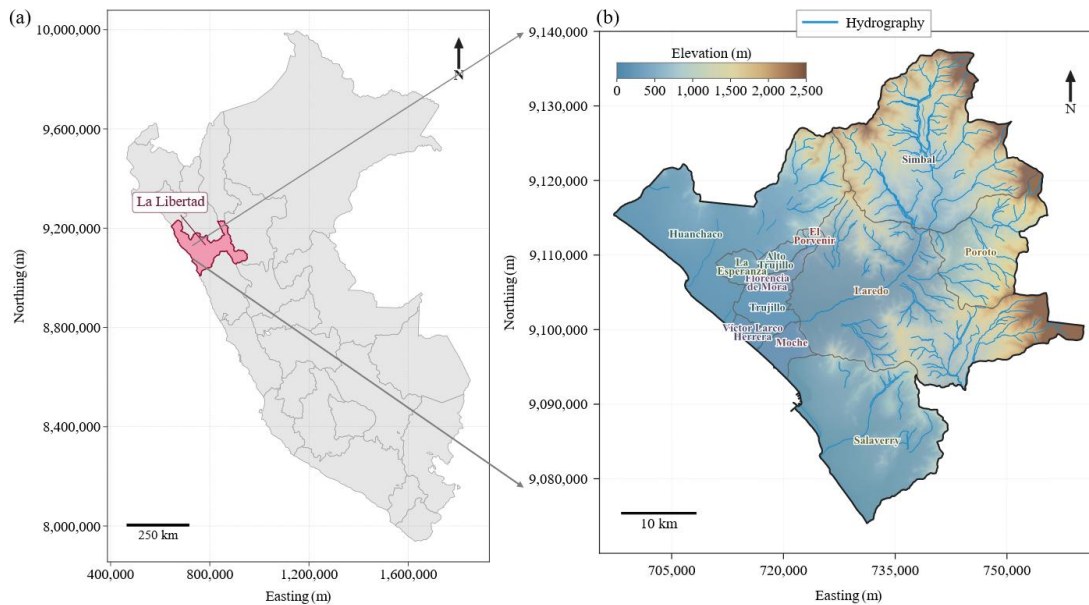


Fig. 1 Location of the study area: (a) location of the department of La Libertad within Peru; (b) province of Trujillo, showing topography, the hydrographic network, and districts

The Moche River constitutes one of the main hydrographic axes of the province. Its flow regime exhibits marked variability associated with precipitation within its basin, and high-flow events can cause overbank flooding and bank erosion. This system is complemented by temporarily active ravines that cross or discharge near occupied areas. The provincial land-use plan identifies the channels of El León, Río Seco, and San Ildefonso among the areas relevant to the assessment of hazards associated with extraordinary rainfall. Therefore, the hydrological setting of the study area encompasses both fluvial processes and runoff originating from ravines, as well as water accumulation in urban sectors (MPT 2016).

The climatic conditions of the coastal urban sector are characterized by semi-warm temperatures, atmospheric humidity, and low rainfall during most of the year. However, these conditions can change considerably during episodes of anomalous ocean warming and changes in atmospheric circulation. CENEPRED (2017) documented that, during the 2017 Coastal El Niño, the districts of Trujillo, Víctor Larco Herrera, and El Porvenir recorded precipitation classified as extremely rainy, exceeding the 99th percentile of the thresholds used in its assessment. This contrast between generally low-rainfall conditions and intense rainfall episodes is fundamental for understanding the occurrence of flooding in the area.

Historical records show the recurrence of these processes. The 1997–1998 El Niño episode caused flooding and damage in different sectors of the province. Subsequently, during the 2017 Coastal El Niño, the activation of the San Ildefonso ravine generated flows and flooding that reached El Porvenir, Florencia de Mora, Trujillo, and Víctor Larco Herrera, while discharges from El León affected areas of Huanchaco and El Milagro. The occupation of natural channels and flow pathways contributed to damage to housing and infrastructure (MPT 2016; Medina et al. 2017).

Recent events confirm the persistence of this problem. On 10 March 2023, intense rainfall activated the Indoamérica ravine in La Esperanza and caused damage to homes, healthcare facilities, educational

institutions, and basic services (INDECI 2023). Likewise, on 29 March 2025, debris flows and flooding were recorded, affecting housing and transportation infrastructure in several districts of the province, including La Esperanza and Laredo (INDECI 2025b).

2.2. Data sources and information preparation

The procedure followed to construct the flood inventory, prepare the predictor variables, train and compare the machine-learning models, assess exposure, and subsequently generate the dynamic maps is summarized in Fig. 2.

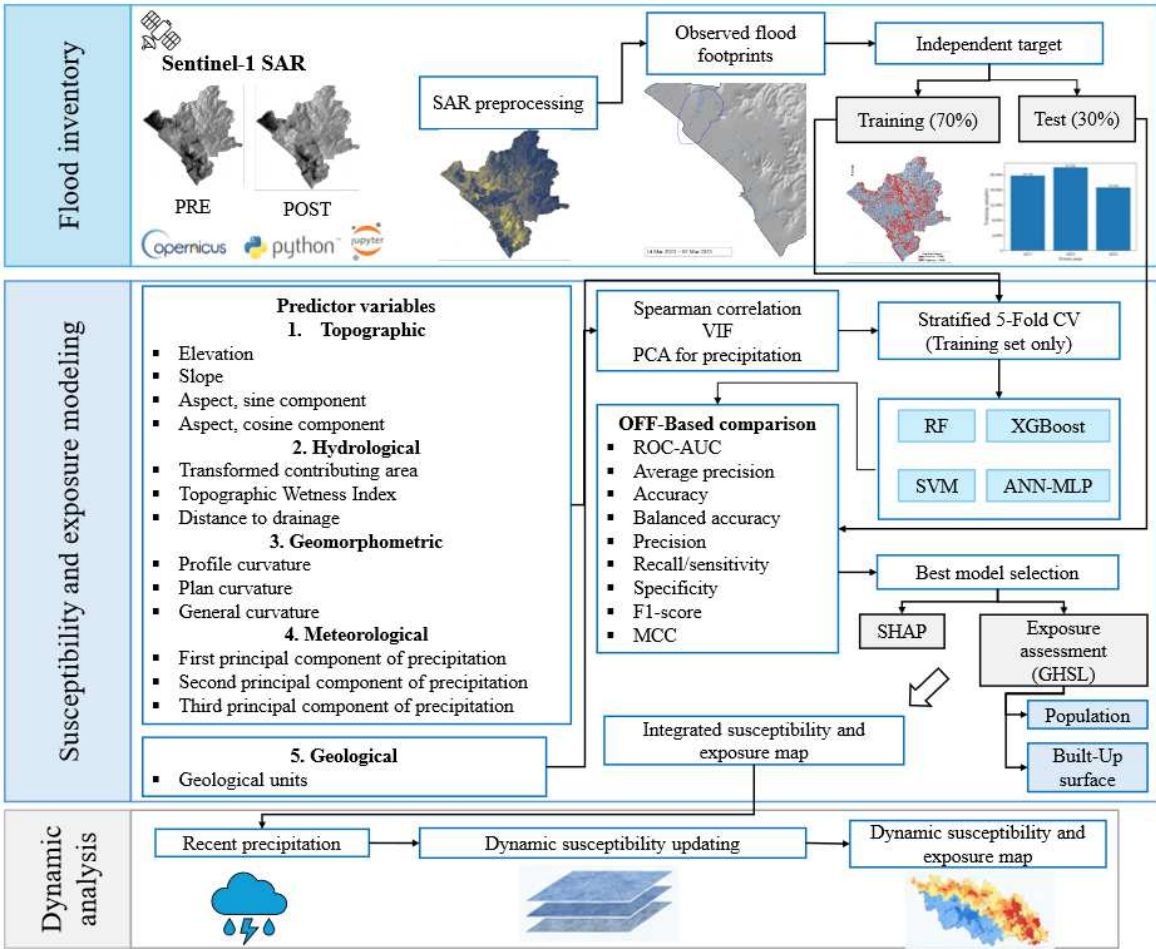


Fig. 2 Research workflow

The predictor variables were grouped into topographic, hydrological, geomorphometric, meteorological, and geological components (Table 1). This type of integration is commonly used in susceptibility mapping, where variables such as elevation, slope, distance to drainage channels, flow accumulation, TWI, precipitation, and lithology have demonstrated the ability to differentiate areas with contrasting hydrological responses (Khosravi et al. 2019; Amiri et al. 2024). All layers were integrated into the WGS 84/UTM Zone 17S coordinate system (EPSG:32717) using a common 30×30 m grid. The spatial distribution of the predictors is presented in the Appendix (Fig. 14).

Table 1 Predictor variables used for flood susceptibility modeling

Class	Name	Variable	Unit	Source
Topographic	Elevation	ELEV	m	DEM GLO-30
	Slope	SLP	°	DEM GLO-30
	Aspect, sine component	ASP-SIN	-	DEM GLO-30
	Aspect, cosine component	ASP-COS	-	DEM GLO-30
Hydrological	Transformed contributing area	LCA	-	DEM GLO-30
	Topographic Wetness Index	TWI	-	DEM GLO-30
	Distance to drainage	DDN	m	DEM GLO-30
Geomorphometric	Profile curvature	PRC	m ⁻¹	DEM GLO-30
	Plan curvature	PLC	m ⁻¹	DEM GLO-30
	General curvature	GEC	m ⁻¹	DEM GLO-30
Meteorological	First principal component of precipitation	PCA_precip_1	PCA	NASA GPM IMERG V07
	Second principal component of precipitation	PCA_precip_2	PCA	NASA GPM IMERG V07
	Third principal component of precipitation	PCA_precip_3	PCA	NASA GPM IMERG V07
Geological	Geological unit	GEOL	Category	INGEMMET

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188 The topographic variables were derived from the Copernicus DEM GLO-30, a product with global coverage
189 and an approximate spatial resolution of 30 m (Poursanidis and Katsanevakis 2025). Elevation represents
190 the altitudinal position of the terrain and makes it possible to distinguish low-lying areas, which may
191 potentially receive runoff, from topographically higher areas, whereas slope describes the inclination of the
192 surface and influences the velocity and persistence of surface flow. Both variables are widely used in flood
193 susceptibility models because of their relationship with the distribution and movement of water (Demissie
194 et al. 2024). Slope and aspect were calculated using local gradients over 3×3 -cell windows following Horn
195 (1981). Because of the circular nature of aspect, it was transformed into two continuous components:

$$ASP - SIN = \sin(\theta) \quad (1)$$

$$ASP - COS = \cos(\theta) \quad (2)$$

196 where θ denotes the azimuth expressed in radians. This transformation avoids the numerical discontinuity
197 between 0° and 360° while preserving the directional information of the terrain.

198 The hydrological variables were derived from the DEM conditioned using the Priority-Flood algorithm, a
199 procedure used to correct depressions that may artificially interrupt drainage continuity (Barnes et al. 2014).
200 Subsequently, the D8 scheme was applied to establish flow direction and determine the contribution of
201 upstream cells (O'Callaghan and Mark 1984). The contributing area represents the surface area capable of
202 supplying runoff to each cell; because of its strongly skewed distribution, it was transformed as follows:

$$LCA = \ln\left(1 + \frac{A_c}{A_0}\right) \quad (3)$$

where A_c is the contributing area and $A_0 = 1\text{km}^2$ is a reference unit. Likewise, the Topographic Wetness Index represents the tendency of the terrain to concentrate water and was calculated following Beven and Kirkby (1979):

$$TWI = \ln\left(\frac{a}{\tan\beta}\right) \quad (4)$$

where a is the specific catchment area and β is the local slope in radians. Finally, distance to drainage represents the proximity of each cell to the flow network, a condition that may favor greater connectivity with areas of overflow or water concentration. Demissie et al. (2024) recognize distance to drainage channels, flow accumulation, and TWI among the most widely used predictors for representing flood susceptibility.

The local geometry of the terrain was represented by profile curvature, plan curvature, and general curvature, calculated from the original 30 m DEM using second-order derivatives over 3×3 -cell windows. PRC describes changes in the surface along the direction of maximum slope and allows the identification of areas where flow may accelerate or decelerate; PLC represents the lateral convergence or divergence of the surface and, therefore, the tendency of water to concentrate or disperse; whereas GEC summarizes the local convexity or concavity of the terrain. The incorporation of curvature variables makes it possible to represent morphological characteristics that are not described solely by elevation and slope (Al-Kindi and Alabri 2024).

Precipitation data were obtained from NASA GPM IMERG V07, a multisatellite product that provides estimates every 30 min on a native $0.1^\circ \times 0.1^\circ$ grid (Batista et al. 2025). For each event, maximum moving accumulations of 1, 3, 6, 12, 24, 48, and 72 h were calculated, together with total event precipitation, allowing both short-duration intense episodes and prolonged accumulations to be represented. Owing to the high correlation among these metrics, they were standardized and reduced using principal component analysis (PCA), fitted exclusively to the training set:

$$PC_k = \sum_{j=1}^p w_{jk} z_j \quad (5)$$

where z_j represents each standardized precipitation variable and w_{jk} its loading on component k . PCA_precip_1, PCA_precip_2, and PCA_precip_3 were retained, jointly explaining 98.29% of the original variance. Precipitation constitutes a particularly relevant predictor because it introduces an event-varying component into the model, unlike relatively permanent terrain factors.

Geological information was obtained from INGEMMET cartography at a scale of 1:50,000 and was reprojected, clipped, and rasterized onto the master grid. The GEOL variable represents the geological units present within the province and was incorporated because lithological characteristics can produce differences in infiltration, permeability, water storage, and runoff generation. Geology is a factor frequently

used together with topographic and hydrological variables in flood susceptibility modeling (Al-Kindi and Alabri 2024).

2.3. Multitemporal Sentinel-1 preprocessing and delineation of observed flood footprints

To spatially reconstruct the floods that occurred in 2017, 2023, and 2025, Sentinel-1 GRD imagery acquired in Interferometric Wide Swath (IW) mode, with VV and VH polarizations, was used. PRE–POST image pairs corresponding to 3 and 15 March 2017, 2 and 14 March 2023, and 27 March and 2 April 2025, respectively, were selected. The images were processed individually through orbit correction, thermal and border noise removal, radiometric calibration to σ^0 , 7×7 -pixel Refined Lee filtering, and Range-Doppler terrain correction. This workflow is consistent with procedures used to prepare Sentinel-1 data for flood detection and multitemporal analysis (Twele et al. 2016; Tsyganskaya et al. 2018). Finally, the values were expressed in decibels, and all acquisitions were reprojected and aligned to the 30 m master grid in WGS 84/UTM Zone 17S.

$$\sigma_{dB}^0 = 10 \log_{10}(\sigma^0) \quad (6)$$

Pixel-level change detection was performed by calculating the difference between the post-event and pre-event conditions for each event. Changes were calculated for both polarizations and their contrast:

$$\Delta W = VV_{POST} - VV_{PRE} \quad (7)$$

$$\Delta VH = VH_{POST} - VH_{PRE} \quad (8)$$

$$\Delta(VV - VH) = (VV - VH)_{POST} - (VV - VH)_{PRE} \quad (9)$$

The PRE–POST analysis enables the identification of changes in radar response occurring during the time interval used to delineate areas affected by flooding with Sentinel-1 (Cian et al. 2018; Li et al. 2018). Over open surfaces covered by water, specular reflection generally reduces the energy returned to the sensor and produces negative values of ΔVV or ΔVH ; however, this behavior is not universal. In urban or vegetated areas, increases in backscatter may occur due to double-bounce mechanisms between water and vertical structures. Fig. 3 illustrates the spatial variation in VV backscatter between pre- and post-event conditions for the Yaku event. Negative ΔVV values represent a decrease in the radar signal relative to the initial state and may be consistent with the appearance of relatively smooth water surfaces; conversely, positive increases indicate enhanced backscatter and may correspond to changes in moisture, roughness, or double-bounce mechanisms in built-up environments.

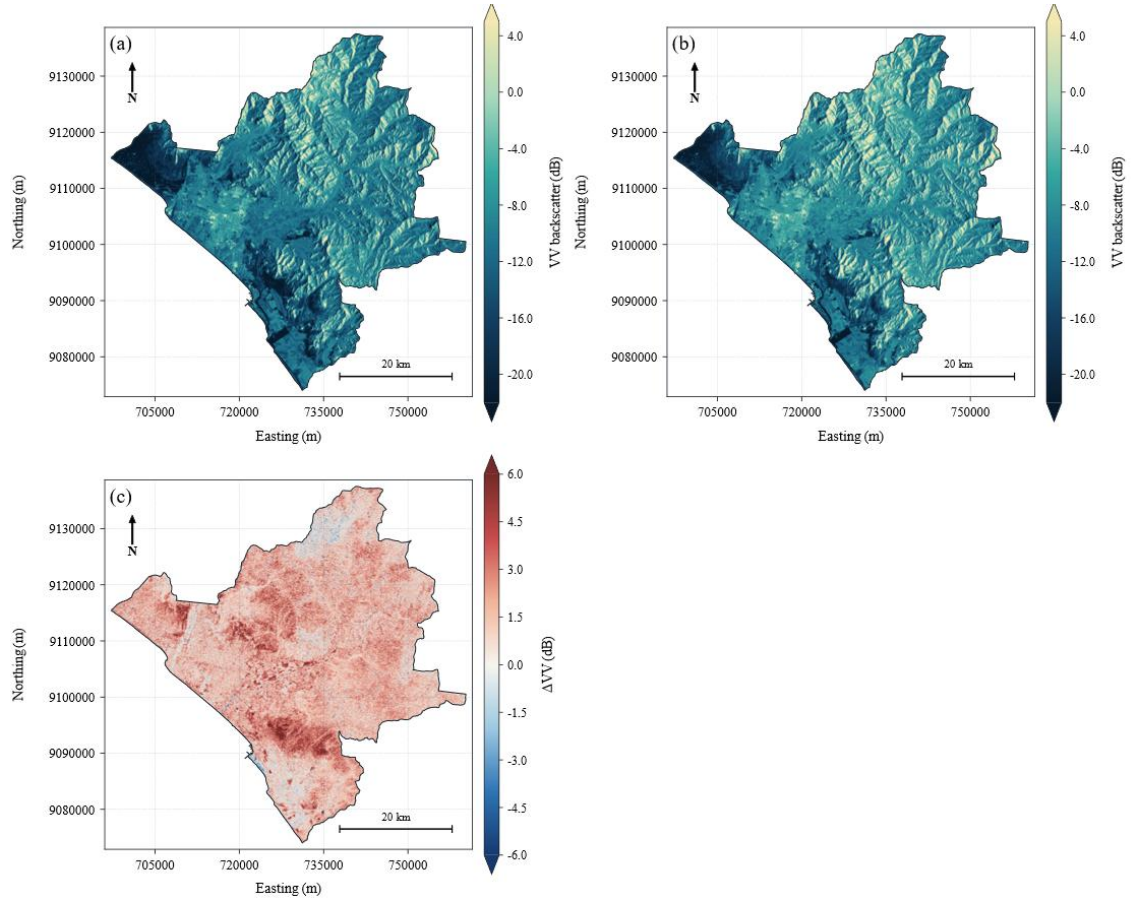


Fig. 3 Multitemporal analysis of Sentinel-1 backscatter during the 2023 Yaku event. (a) σ_W^0 backscatter under pre-event conditions, 2 March 2023; (b) σ_W^0 backscatter under post-event conditions, 14 March 2023; and (c) temporal change in backscatter, $\Delta VV = VV_{POST} - VV_{PRE}$. Values are expressed in dB

To obtain the observed flood footprints, SAR changes were robustly standardized using the median and the median absolute deviation (MAD), thereby reducing the influence of extreme values:

$$Z_A^* = \frac{\Delta - \text{median}(\Delta)}{\text{MAD}(\Delta)} \quad (10)$$

The resulting anomalies of ΔVV , ΔVH and $\Delta(VV - VH)$ were combined and subsequently constrained using broad geomorphological criteria based on height above nearest drainage (HAND), slope, and distance to the drainage network, with the aim of excluding radar changes located in areas inconsistent with the expected dynamics of flooding. The combined use of multitemporal SAR changes and topographic information helps reduce false positives associated with surface roughness, vegetation, or terrain characteristics (Ushanin et al. 2024). These footprints were used exclusively as observed evidence to construct the target variable for machine learning and not as predictors, thereby avoiding the incorporation of event information that subsequently had to be estimated by the model. The observed flood footprints are shown in Fig. 4.

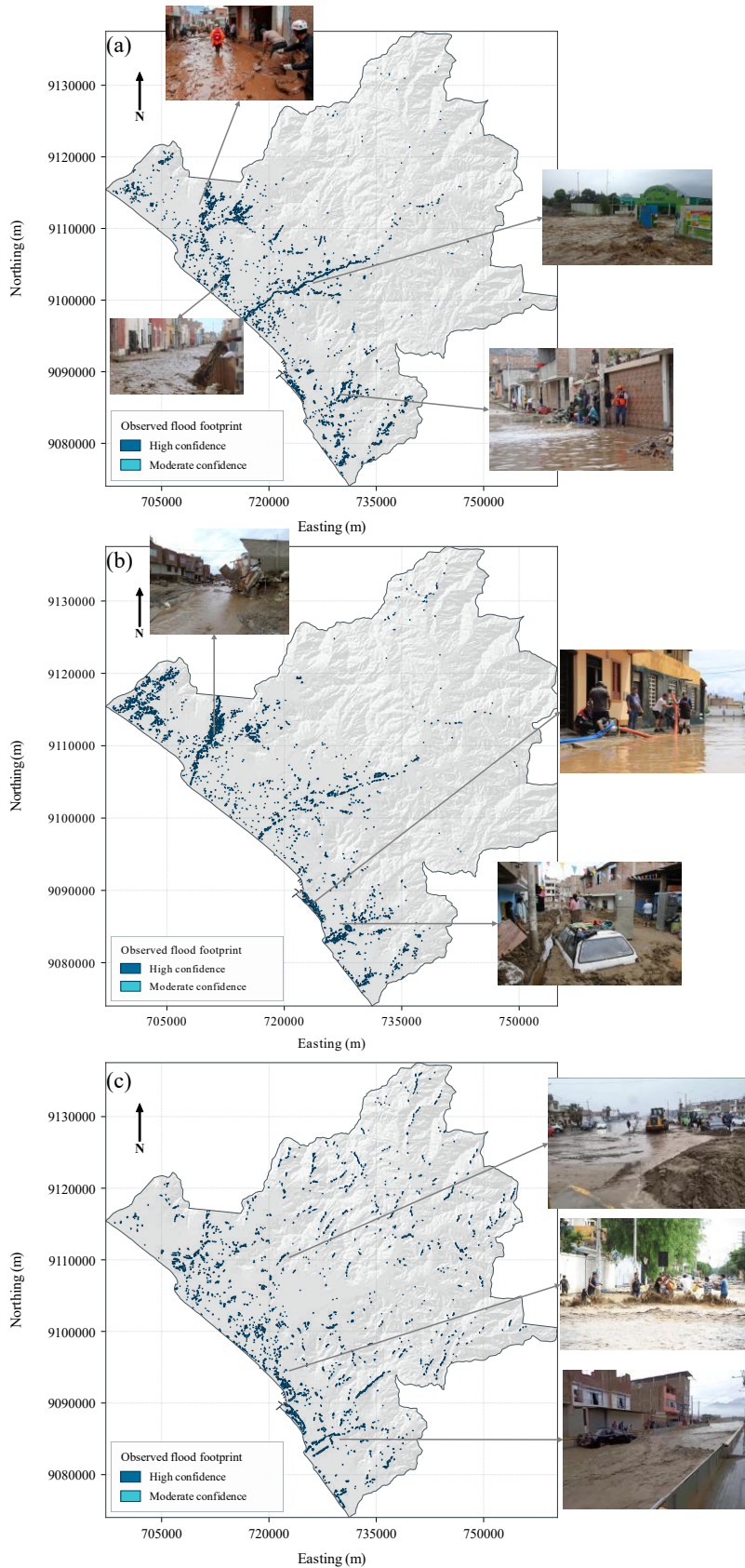


Fig. 4. Observed flood footprints derived from the multitemporal analysis of Sentinel-1. (a) 2017 Coastal El Niño, based on the 3–15 March image pair; (b) the 2023 Yaku event, based on the 2–14 March image pair; and (c) the 2025 intense rainfall event, based on the 27 March–2 April image pair

2.4. Sampling and data partitioning

From the independent flood footprints of the 2017, 2023, and 2025 events, positive samples corresponding to areas observed as affected and negative samples from sectors without evidence of flooding were extracted, after first excluding areas considered ambiguous. To reduce redundancy among neighboring pixels of the 30 m grid, sampling was limited to a maximum of one observation per 90×90 m block. Subsequently, each event was balanced at a 1:1 ratio between the positive and negative classes, preventing the greater availability of non-flooded pixels from influencing classifier learning. Spatial thinning was used solely to reduce the immediate dependence among nearby observations and does not constitute independent spatial validation, which would require an explicit separation between training and evaluation areas (Roberts et al. 2017).

The combined dataset was divided using stratified random sampling, simultaneously preserving the proportion of each event and the balance between classes. Seventy percent of the observations were assigned to the training set and the remaining 30% to a held-out test set, a strategy widely used to separate model fitting from subsequent evaluation (Vabalas et al. 2019; Wahba et al. 2024). The procedure yielded 58338 training samples and 25002 test samples, with equal numbers of positive and negative observations in both partitions (Table 2).

Table 2 Distribution of positive and negative samples from the three events between the training (70%) and test (30%) sets

Event	Train positive	Train negative	Test positive	Test negative	Total
2017	9877	9877	4233	4233	28220
2023	10963	10963	4699	4699	31324
2025	8329	8329	3569	3569	23796
Total	29169	29169	12501	12501	83340

2.5. Cross-validation and machine-learning models

Model fitting and internal comparison were performed exclusively using the training set through stratified five-fold cross-validation (5-fold CV). The observations were distributed into five subsets while preserving the proportion of positive and negative classes. In each iteration, four partitions were used to fit the model and the remaining partition was used for validation, repeating the procedure until each partition had served once as the validation set. For a metric M , mean performance was calculated as:

$$\bar{M}_{CV} = \frac{1}{5} \sum_{k=1}^5 M_k \quad (11)$$

where M_k corresponds to the value obtained in partition k . The same fold assignment was used for all algorithms, allowing their comparison under equivalent conditions. Likewise, out-of-fold (OOF) predictions were retained so that each training sample was predicted only by a model that had not used it during fitting. The test set remained completely excluded from cross-validation and hyperparameter tuning

and was reserved for final evaluation. This scheme makes efficient use of the training data while maintaining internal evaluation on observations not used in each fit (Varoquaux 2018; Asrade et al. 2026).

Random Forest (RF), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), and Artificial Neural Network–Multilayer Perceptron (ANN-MLP) were evaluated. These algorithms represent different learning approaches (bagging ensemble, boosting, sequential learning, margin maximization, and neural networks), allowing their ability to represent nonlinear relationships among topographic, hydrological, geological, and meteorological conditions and the observed occurrence of flooding to be compared. The comparative use of RF, XGBoost, SVM, and neural networks is widely documented in flood susceptibility mapping (Demissie et al. 2024; Li et al. 2026).

Random Forest (RF) constructs an ensemble of decision trees from bootstrap samples and randomly selects a subset of variables at each split, reducing correlation among trees and improving its generalization ability (Breiman, 2001). For binary classification, the estimated flood probability can be expressed as:

$$\hat{P}_{RF}(y = 1|x) = \frac{1}{B} \sum_{b=1}^B I[h_b(x) = 1] \quad (12)$$

where B is the number of trees, $h_b(x)$ is the prediction of tree b , and $I(\cdot)$ is an indicator function. RF was included because of its ability to represent nonlinear relationships and interactions among predictors without imposing a predefined functional form, a characteristic that has favored its application in flood susceptibility mapping (Breiman 2001).

XGBoost constructs trees sequentially, such that each new tree seeks to reduce the residual errors accumulated by the preceding trees. The additive model can be represented as:

$$F_t(x) = F_{t-1}(x) + \eta f_t(x) \quad (13)$$

where F_{t-1} is the accumulated prediction, f_t is the new tree, and η is the learning rate. Its training minimizes an objective function that combines prediction error with a complexity penalty:

$$\mathcal{L} = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{t=1}^T \Omega(f_t) \quad (14)$$

where l is the loss function and Ω regularizes tree complexity. This regularization, together with sequential learning, helps control overfitting and represent complex relationships among geospatial variables (Chen and Guestrin 2016).

Support Vector Machine (SVM) seeks a decision boundary that maximizes the margin between flooded and non-flooded classes. To represent nonlinear separations, a radial basis function (RBF) was used, whose decision rule can be expressed as:

$$f(x) = \text{sign} \left[\sum_{i=1}^n \alpha_i y_i \exp(-\gamma \|x - x_i\|^2) + b \right] \quad (15)$$

where α_i are the coefficients associated with the support vectors, y_i are their classes, γ controls the width of the kernel, and b represents the intercept. The RBF kernel enables flexible decision boundaries to be constructed when class separation cannot be described by a linear relationship (Cortes and Vapnik 1995).

The ANN-MLP was structured as a feed-forward neural network composed of an input layer, one or more fully connected hidden layers, and an output layer. For each hidden layer, the transformation is expressed as:

$$h^{(l)} = \phi(W^{(l)}h^{(l-1)} + b^{(l)}) \quad (16)$$

where $W^{(l)}$ and $b^{(l)}$ represent the weights and biases of layer l , and ϕ is its activation function. In the binary output layer, the probability of belonging to the flooded class is obtained as:

$$\hat{p}_i = \sigma(W_0 h^{(L)} + b_0) \quad (17)$$

where $\sigma(\cdot)$ corresponds to the sigmoid function. The network parameters are adjusted through backpropagation, progressively reducing the error between the predictions and the observed classes (Rumelhart et al. 1986). The ANN-MLP was included because it allows nonlinear interactions among multiple predictors to be learned without specifying the form of those relationships in advance.

2.6. Métricas de evaluación

Model performance was evaluated using complementary metrics derived from the confusion matrix and predicted probabilities. True positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) were considered. In addition to metrics dependent on a classification threshold, ROC-AUC and Average Precision were used to evaluate discriminatory performance across different thresholds (Fawcett 2006; Saito and Rehmsmeier 2015).

ROC-AUC represents the area under the curve relating sensitivity and the false positive rate:

$$ROC - AUC = \int_0^1 TPR(FPR) dFPR \quad (18)$$

whereas Average Precision (AP) summarizes the precision–recall curve:

$$AP = \sum_n (R_n - R_{n-1}) P_n \quad (19)$$

where P_n and R_n correspond to precision and recall at each threshold. AP complements ROC-AUC by focusing specifically on the performance of the positive class.

The metrics based on binary classification were calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (20)$$

$$Balanced Accuracy = \frac{1}{2} \left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right) \quad (21)$$

$$Precision = \frac{TP}{TP + FP} \quad (22)$$

$$Recall (Sensitivity) = \frac{TP}{TP + FN} \quad (23)$$

$$Specificity = \frac{TN}{TN + FP} \quad (24)$$

$$F1 = 2 \frac{Precision \times Recall}{Precision + Recall} \quad (25)$$

Finally, the Matthews Correlation Coefficient (MCC) was calculated, integrating all four components of the confusion matrix and providing an overall measure of agreement between the observed and predicted classes:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (26)$$

MCC ranges from -1 to 1 , where 1 indicates perfect classification, 0 indicates performance with no association, and -1 indicates complete disagreement; it is particularly useful as a complementary measure to accuracy and F1 (Chicco and Jurman 2020).

2.7. Model interpretation using SHAP

The contribution of the predictors in the selected model was interpreted using SHapley Additive exPlanations (SHAP), which assigns a contribution value to each variable for each prediction based on Shapley value theory (Lundberg and Lee 2017). A positive SHAP value indicates that the variable shifts the prediction toward higher susceptibility, whereas a negative value reduces it relative to the model's expected value. For a variable j , its contribution is expressed as:

$$\phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|! (M - |S| - 1)!}{M!} [f_{S \cup \{j\}}(x) - f_S(x)] \quad (27)$$

where F is the set of predictors, M is their total number, and S is each subset does not contain variable j .

2.8. Exposure assessment using GHSL

Exposure was assessed using GHS-POP R2023A and GHS-BUILT-S R2023A from the Global Human Settlement Layer (GHSL), obtained through Google Earth Engine. GHS-POP represents the resident population per cell, whereas GHS-BUILT-S quantifies the built-up surface; both products are available at temporal intervals of five years (SCHIAVINA et al. 2023). To facilitate their spatial comparison, population was transformed into density and built-up surface into percentage:

$$D_i = \frac{P_i}{A_i}, \quad BU_i = 100 \frac{S_i}{A_i} \quad (28)$$

where P_i is the population of the cell, S_i is the built-up surface, A_i is the cell area, D_i is the population density, and BU_i is the built-up percentage. The GHSL epochs closest to each event were used: 2015 for 2017, 2020 for 2023, and 2025 for 2025. Subsequently, both layers were aligned with the 30 m grid solely

for spatial integration, without attributing to them an effective resolution higher than the original. The 2025 epoch of version R2023A should be regarded as a modeled estimate, because the future 2025–2030 periods were obtained through spatiotemporal extrapolation procedures.

$$PopExp_c = \sum_{i \in c} D_i A_i, \quad BuiltExp_c = \sum_{i \in c} \frac{BU_i}{100} A_i \quad (29)$$

2.9. Dynamic updating of susceptibility

The dynamic component was incorporated by updating the precipitation variables derived from GPM IMERG V07, while the topographic, hydrological, and geological factors remained constant. IMERG provides precipitation estimates every 30 min on a $0.1^\circ \times 0.1^\circ$ grid, allowing meteorological conditions to be updated as new observations become available. For each time step t , the 1, 3, 6, 12, 24, 48, and 72 h accumulations and the event-total accumulation were recalculated. These variables were standardized using exclusively the parameters obtained during training:

$$z_{j,t}(x) = \frac{R_{j,t}(x) - \mu_j^{train}}{\sigma_j^{train}} \quad (30)$$

and subsequently projected using the loadings of the previously fitted PCA:

$$PC_{k,t}(x) = \sum_{j=1}^p w_{jk}^{train} z_{j,t}(x) \quad (31)$$

Finally, the new meteorological components were combined with the static predictors and introduced into the final model to obtain updated susceptibility:

$$S_t(x) = \hat{f}[X_{static}(x), PC_{1,t}(x), PC_{2,t}(x), PC_{3,t}(x)] \quad (32)$$

where $S_t(x)$ represents the estimated susceptibility probability for cell x at time t . Thus, the model is not retrained with each update; only the meteorological variables are updated and inference is rerun using the previously trained model. This approach enables a transition from a static representation to susceptibility conditioned by the recent state of precipitation, a principle used in recent dynamic flood-mapping approaches (Mosaffa and Brocca 2024).

3. Results

3.1. Dependence among predictors and reduction of precipitation information

The Spearman correlation matrix showed associations of varying magnitude among the continuous predictors (Fig. 5). The strongest relationships were observed between elevation and slope ($\rho = 0.81$), profile curvature and general curvature ($\rho = -0.79$), plan curvature and general curvature ($\rho = -0.77$), and slope and TWI ($\rho = -0.74$). Associations were also observed between LCA and plan curvature ($\rho = -0.71$), LCA and general curvature ($\rho = 0.63$), and elevation and TWI ($\rho = -0.61$). In contrast, the precipitation components showed low correlations with most terrain variables. Although relatively high associations were observed among some geomorphometric and topographic predictors, these alone did not imply problematic multicollinearity.

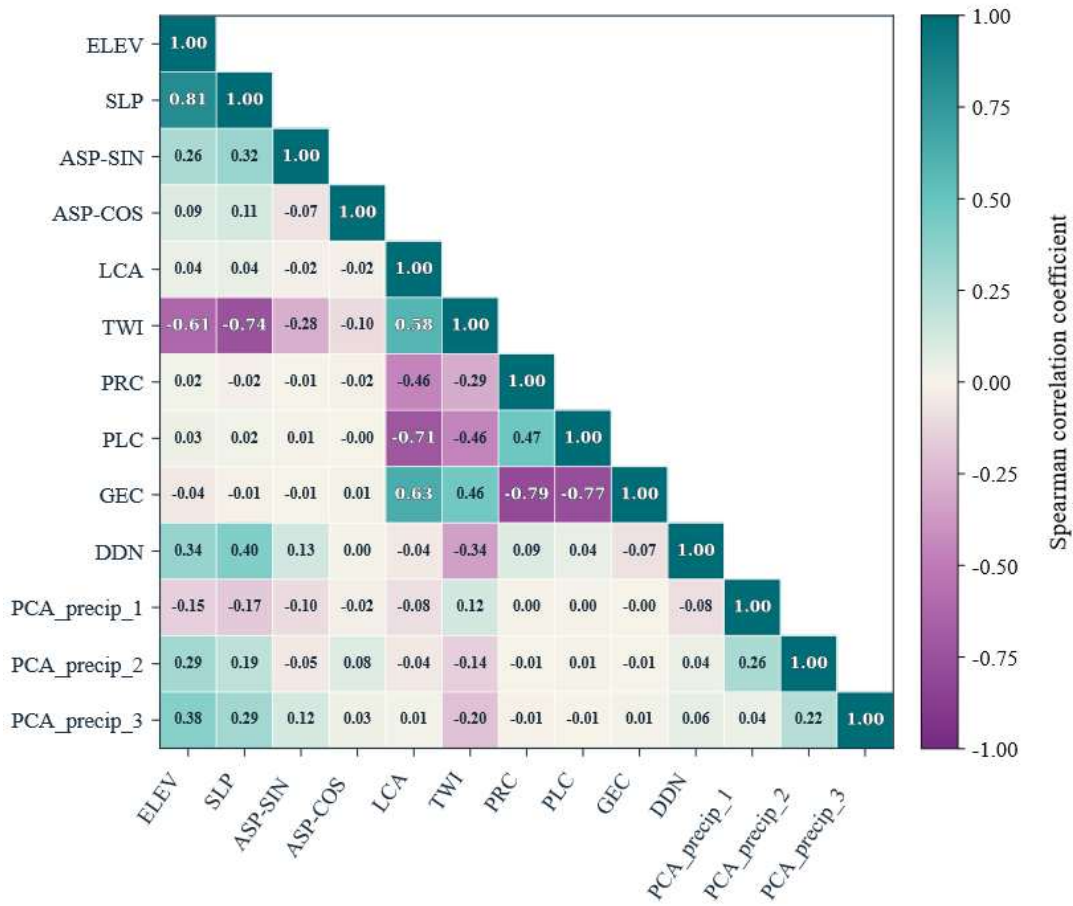


Fig. 5 Correlation structure among the continuous predictor variables

The variance inflation factor diagnostic confirmed low multicollinearity in the final predictor set (Fig. 6a). All values remained below 5, with the highest values corresponding to TWI (3.84), slope (3.43), general curvature (2.95), plan curvature (2.47), and elevation (2.18); the remaining variables showed values below 2. This indicates that, despite some relatively high bivariate correlations, no variable reached levels that would justify its exclusion due to linear redundancy.

The PCA applied to the eight precipitation metrics concentrated most of the information into three components (Fig. 6b–c). PC1 explained 86.38% of the variance, PC2 6.76%, and PC3 5.15%, jointly accounting for 98.29%. PC1 showed positive and similar loadings across the different accumulation windows, with greater contributions from P48h, P24h, P72h, and P06h, and therefore mainly represented the overall pattern of precipitation magnitude. PC2 contrasted total event accumulation and prolonged windows with short-duration accumulations, whereas PC3 was mainly influenced by P01h and showed opposite contributions from P12h and P24h. Thus, the three components retained both the overall precipitation signal and differences among temporal scales, while reducing the redundancy present in the original accumulation metrics.

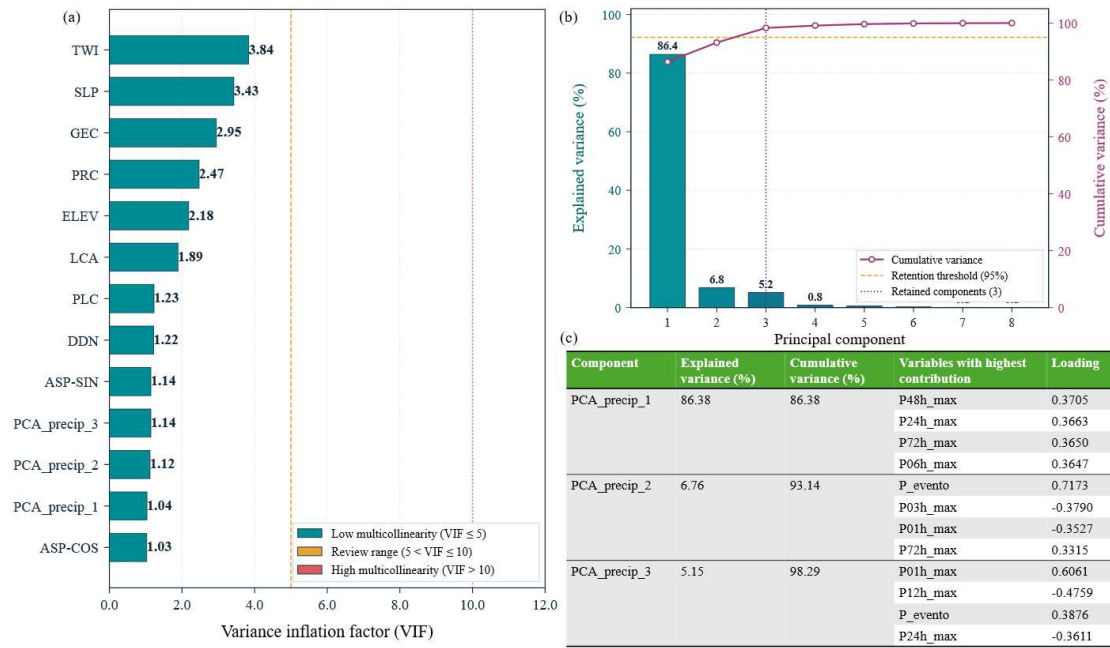


Fig. 6 Multicollinearity diagnostics and dimensionality reduction of the precipitation variables. (a) Variance inflation factor (VIF) of the continuous predictors; (b) individual and cumulative variance explained by the principal precipitation components; and (c) loadings of the original variables with the greatest contributions to PC1, PC2, and PC3

3.2. Model hyperparameter configuration and selection

The hyperparameter search produced distinct configurations for the four algorithms (Table 3). For Random Forest, the selected configuration retained trees with unrestricted depth, 700 estimators, and a maximum sample fraction of 0.90, with $max_features = 0.35$, promoting diversity among trees. XGBoost selected a learning rate of 0.04, a maximum depth of 8, and 1400 iterations, together with L1 regularization = 0.01 and L2 regularization = 5.0, which helped control model complexity during sequential learning. For SVM, the final configuration used $C = 10$, $\gamma = 0.02222$ and 400 Nyström components to approximate the RBF kernel. Finally, the ANN-MLP selected two hidden layers with 96 and 48 neurons, ReLU activation, the Adam optimizer, and an initial learning rate of 0.002.

Table 3 Search space and selected configuration of the machine-learning models

Model	Hyperparameter	Evaluated values	Selected configuration
Random Forest	<i>max_depth</i>	[12, 18, 24, 32, None]	None
	<i>min_samples_split</i>	[2, 5, 10, 20]	2
	<i>min_samples_leaf</i>	[1, 2, 4, 8]	2
	<i>max_features</i>	[sqrt, 0.35, 0.50, 0.70]	0.35
	<i>max_samples</i>	[0.75, 0.90, 1.00]	0.90
	Criterion	Gini	Gini
	Trees	[Stage 1: 160; Stage 2: 400]	700
XGBoost	<i>eta</i>	[0.025, 0.04, 0.06, 0.08, 0.10]	0.04

	<i>max_depth</i>	[3, 4, 5, 6, 8]	8
	<i>min_child_weight</i>	[1, 3, 5, 8]	8
	<i>subsample</i>	[0.70, 0.85, 1.00]	0.85
	<i>colsample_bytree</i>	[0.60, 0.75, 0.90, 1.00]	0.90
	<i>gamma</i>	[0.00, 0.05, 0.15, 0.30]	0.05
	<i>reg_alpha</i>	[0.00, 0.01, 0.10, 0.50]	0.01
	<i>reg_lambda</i>	[1.0, 2.0, 5.0, 10.0]	5.0
	Boosting rounds	[Stage 1: ≤ 700 ; Stage 2: ≤ 1400]	1400
SVM	<i>C</i>	[0.05, 0.10, 0.30, 1.0, 3.0, 10.0]	10.0
	<i>gamma_factor</i>	[0.25, 0.50, 1.0, 2.0, 4.0]	1.0
	γ	Derived from <i>gamma_factor</i> / p , con $p = 45$	0.0222
	Nyström components	[Stage 1: 180; Stage 2: 400]	400
	Maximum iterations	5000	5000
	Tolerance	0.0001	0.0001
ANN-MLP	Hidden architecture	[(32), (64), (128), (64,32), (96,48), (128,64), (128,64,32)]	(96, 48)
	<i>alpha</i>	[0.00001, 0.0001, 0.001, 0.01]	0.0001
	<i>learning_rate_init</i>	[0.0003, 0.0007, 0.001, 0.002]	0.002
	Activation function	ReLU	ReLU
	Optimizer	Adam	Adam
	<i>batch_size</i>	256	256
	Final model epochs	96	96

3.3. Predictive performance and final model selection

The four algorithms showed clear differences in performance, with Random Forest achieving the best results during cross-validation: ROC-AUC of 0.9105, AP of 0.9063, accuracy of 0.8307, and F1-score of 0.8330, followed closely by XGBoost. This advantage was maintained in the independent test set, where RF achieved ROC-AUC = 0.9166, AP = 0.9116, accuracy = 0.8371, precision = 0.8284, sensitivity = 0.8504, specificity = 0.8239, and F1-score = 0.8393 (Table 4). XGBoost showed similar results, whereas ANN-MLP and SVM exhibited lower discriminatory performance. Although RF showed nearly perfect performance on the training data, the similarity between its cross-validation and test results indicates that its predictive capacity was maintained on observations not used during model fitting. Consequently, RF was selected as the final model based on its cross-validation performance, and its behavior was subsequently corroborated using the test set.

Table 4 Predictive performance of the machine-learning models in training, cross-validation, and testing

Metric	Group	Random Forest	XGBoost	SVM	ANN
ROC AUC	Training	0.9998	0.9858	0.8154	0.9209
	CV	0.9105	0.9054	0.8096	0.8577
	Test	0.9166	0.9099	0.8065	0.8611
Average precisión	Training	0.9998	0.9857	0.7936	0.915
	CV	0.9063	0.8983	0.785	0.8403
	Test	0.9116	0.9034	0.7821	0.8427
PR-AUC	Training	0.9998	0.9857	0.7936	0.915
	CV	0.9063	0.8983	0.7849	0.8402
	Test	0.9116	0.9034	0.7821	0.8427
Accuracy	Training	0.9929	0.9386	0.7411	0.8383
	CV	0.8307	0.8259	0.7369	0.7785
	Test	0.8371	0.8301	0.7345	0.7822
Balanced accuracy	Training	0.9929	0.9386	0.7411	0.8383
	CV	0.8307	0.8259	0.7369	0.7785
	Test	0.8371	0.8301	0.7345	0.7822
Precision	Training	0.9923	0.9287	0.7171	0.8272
	CV	0.8221	0.816	0.7137	0.7684
	Test	0.8284	0.8201	0.7114	0.7704
Recall / sensitivity	Training	0.9935	0.9502	0.7962	0.8554
	CV	0.8442	0.8414	0.7913	0.7972
	Test	0.8504	0.8457	0.7892	0.8039
F1-score	Training	0.9929	0.9393	0.7546	0.8411
	CV	0.833	0.8285	0.7505	0.7825
	Test	0.8393	0.8327	0.7483	0.7868
Specificity	Training	0.9923	0.927	0.686	0.8212
	CV	0.8173	0.8103	0.6825	0.7597
	Test	0.8239	0.8145	0.6799	0.7604
MCC	Training	0.9858	0.8775	0.4851	0.6771
	CV	0.6617	0.652	0.4766	0.5573
	Test	0.6745	0.6605	0.4719	0.5649

The curves confirmed the differences observed in the overall performance metrics. Random Forest showed the highest discriminatory ability, with a ROC-AUC of 0.9166, followed by XGBoost (0.9099), ANN-MLP (0.8611), and SVM (0.8065). The same pattern was observed for the precision–recall curve, with AP values of 0.9116, 0.9034, 0.8427, and 0.7821, respectively. The close performance of RF and XGBoost indicates that both models were competitive, although RF consistently maintained the highest values for both curves (see Fig. 7).

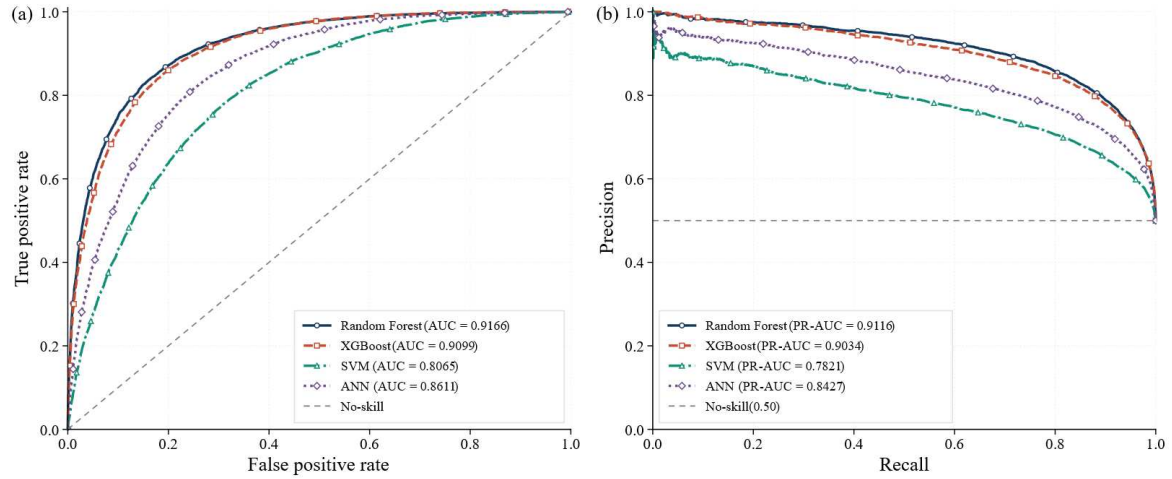


Fig. 7 Discriminatory performance of the models on the independent test set. (a) ROC curves and ROC-AUC values; (b) precision–recall curves and average precision (AP) values

Random Forest correctly classified 85.0% of the susceptible samples and 82.4% of the non-susceptible samples, with 1870 false negatives and 2202 false positives. XGBoost showed similar performance, with 84.6% and 81.4% correct classification for the two classes, respectively. ANN-MLP achieved 80.4% sensitivity and 76.0% specificity, whereas SVM showed the highest proportion of false positives, incorrectly classifying 32.0% of the negative samples as susceptible. Overall, the confusion matrix confirms that RF maintained the best balance between identifying susceptible areas and correctly excluding non-susceptible areas (see Table 5).

Table 5 Confusion matrices of the machine-learning models on the independent test set

Model			Predicted class	
			Non-susceptible	Susceptible
Observed class	Random Forest	Non-susceptible	10299 (82.4%)	2202 (17.6%)
		Susceptible	1870 (15.0%)	10631 (85.0%)
	XGBoost	Non-susceptible	10182 (81.4%)	2319 (18.6%)
		Susceptible	1929 (15.4%)	10572 (84.6%)
	SVM	Non-susceptible	8499 (68.0%)	4002 (32.0%)
		Susceptible	2635 (21.1%)	9866 (78.9%)
	ANN	Non-susceptible	9506 (76.0%)	2995 (24.0%)
		Susceptible	2451 (19.6%)	10050 (80.4%)
Total (predicted)			25002	25002

3.4. Spatial patterns of susceptibility and SHAP analysis

The probability maps show that flood susceptibility is not uniformly distributed across the province of Trujillo. In 2017 and 2023, the highest probabilities were concentrated mainly in low-lying and transitional areas of the coastal valley, as well as in sectors close to drainage channels and ravines, whereas much of the eastern area showed low values. In 2025, the spatial response was more widespread and heterogeneous,

with a greater presence of intermediate and high probabilities in central and eastern areas, suggesting a stronger influence of the meteorological conditions of that event on the final distribution of susceptibility. Overall, the three maps reveal a consistent spatial structure, although modulated by variations in precipitation among events (Fig. 8).

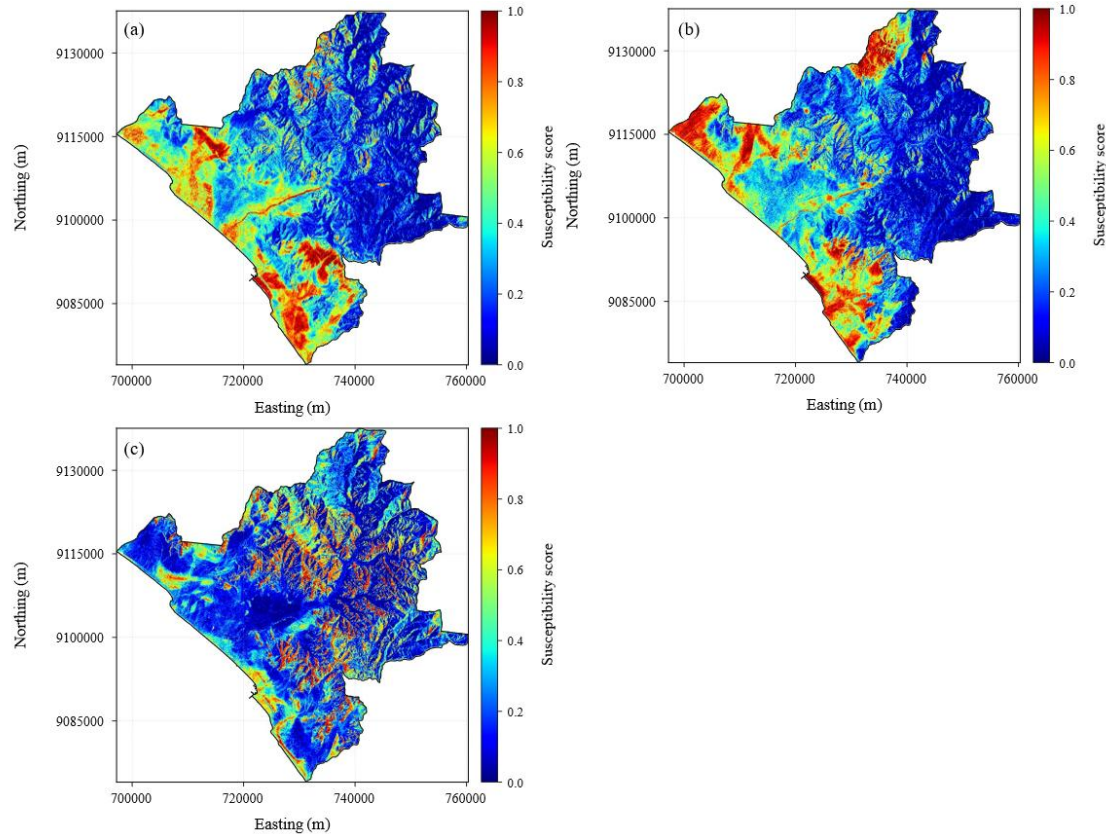


Fig. 8 Spatial distribution of flood susceptibility probability estimated using Random Forest. (a) 2017; (b) 2023; and (c) 2025

The reclassification of probabilities into five levels made it possible to synthesize the spatial patterns into interpretable categories for territorial analysis. In all three years, the high and very high classes tended to concentrate in piedmont sectors, preferential drainage zones, and areas of lower relative elevation, whereas the very low and low classes predominated over broad areas of the eastern sector. The comparison across years shows that 2017 and 2023 present a relatively similar distribution of the extreme classes, whereas 2025 exhibits a more fragmented configuration, with an expansion of the moderate to very high classes toward inland areas (Fig. 9).

The SHAP analysis showed that the variables with the greatest global influence on the model output were ASP-SIN, PC1, PC2, ELEV, PC3, and SLP, followed by ASP-COS, DDN, and GEO. This indicates that the estimated susceptibility was primarily controlled by the combination of terrain orientation, precipitation conditions summarized by PCA, and topographic attributes. In general terms, high values of ASP-SIN tended to increase the predicted susceptibility, whereas the contribution of the precipitation components and elevation showed nonlinear and context-dependent patterns. Variables such as TWI, GEC, PLC, PRC, and LCA showed a smaller contribution, although they were still useful for refining the spatial response of

the model. Overall, SHAP supports that the final RF prediction did not depend on a single factor, but rather on the interaction between topographic control and meteorological forcing (Fig. 10).

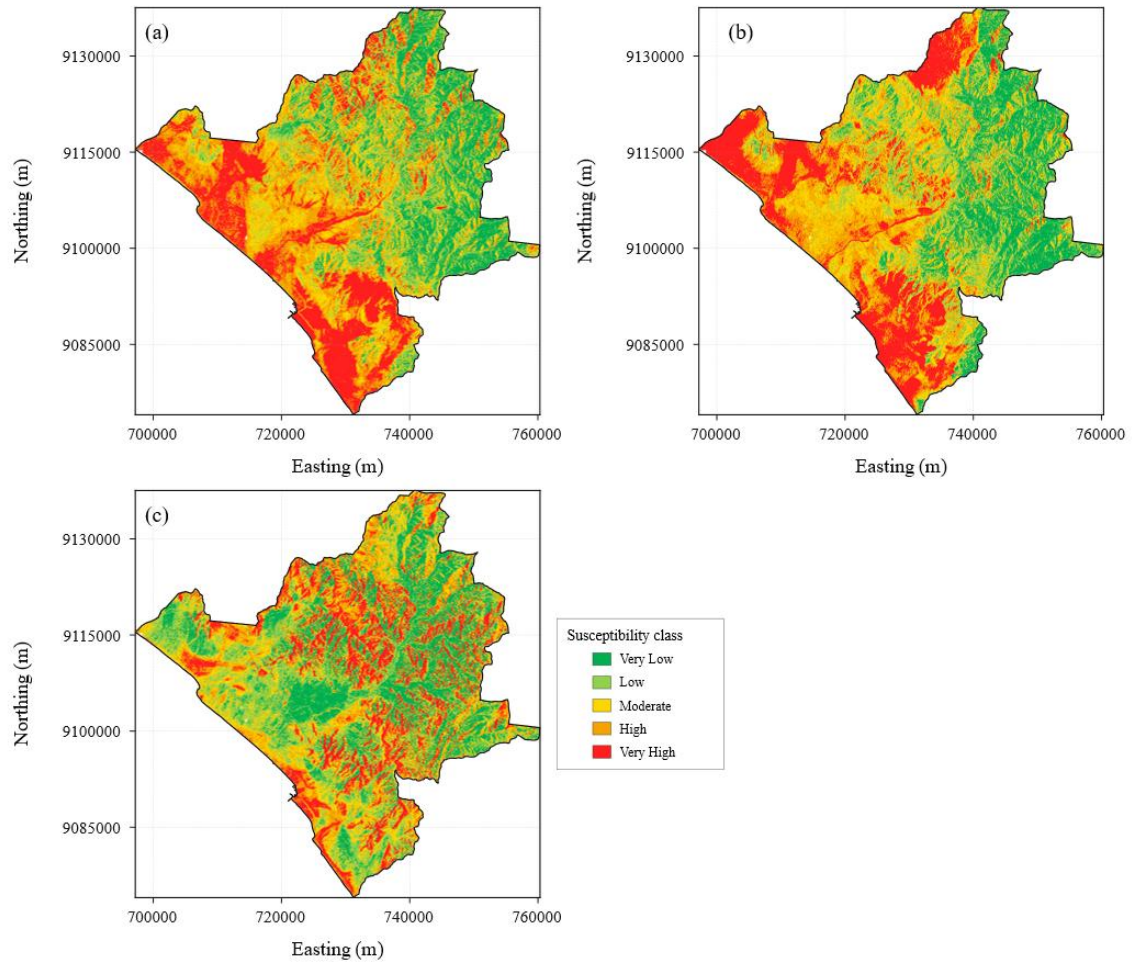


Fig. 9 Spatial classification of flood susceptibility derived from the Random Forest model. (a) 2017; (b) 2023; and (c) 2025

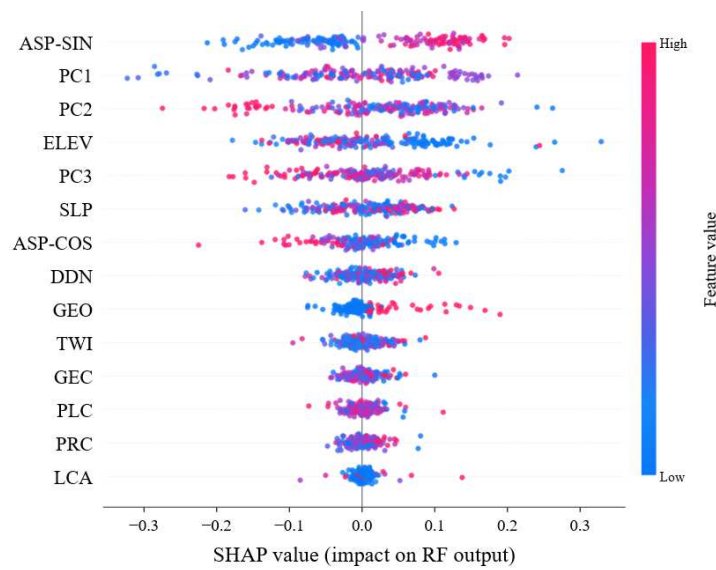


Fig. 10 Interpretation of the Random Forest model using SHAP

3.5. Population and built-up exposure associated with susceptibility

Exposure showed clear differences among the three temporal scenarios. In 2017, the high + very high classes encompassed 792.24 km² and accounted for 52.95% of the population and 56.42% of the built-up surface, indicating the greatest overlap between high susceptibility and human occupation. In 2023, exposure shifted partially toward intermediate classes: the moderate class alone accounted for 53.04% of the population and 46.38% of the built-up surface, whereas the combined high + very high classes represented 37.86% of the population and 44.57% of the built-up surface. In 2025, exposure decreased markedly in the most critical classes, as the high + very high classes accounted for only 11.64% of the population and 13.54% of the built-up surface, whereas the very low + low classes contained most of the population (63.39%) and built-up surface (61.70%). Overall, these results show that the intensity of exposure depended not only on the spatial extent of susceptibility, but also on its overlap with urbanized and densely populated areas (Table 6).

Table 6 Distribution of area, population, and built-up surface according to the flood susceptibility class estimated using Random Forest

Event	GHLS	Susceptibility class	Area (km ²)	Population (n)	Population (%)	Built-up surface (km ²)	Built-up surface (%)
2017	2015	Very low	307.47	4,033	0.42	0.232	0.87
		Low	316.32	71,090	7.36	1.914	7.2
		Moderate	349.86	379,349	39.27	9.44	35.51
		High	419.42	401,009	41.51	10.472	39.39
		Very high	372.82	110,500	11.44	4.527	17.03
		High + Very high	792.24	511,509	52.95	14.999	56.42
2023	2020	Very low	337.12	6,434	0.61	0.369	1.36
		Low	323.98	89,462	8.49	2.083	7.69
		Moderate	371.61	558,762	53.04	12.57	46.38
		High	361.32	363,679	34.52	9.92	36.61
		Very high	371.87	35,142	3.34	2.158	7.96
		High + Very high	733.18	398,820	37.86	12.078	44.57
2025	2025	Very low	415.11	190,090	16.94	4.611	16.95
		Low	419.18	521,129	46.45	12.173	44.75
		Moderate	338.08	280,071	24.96	6.737	24.76
		High	278.7	107,192	9.55	2.787	10.24
		Very high	314.83	23,429	2.09	0.897	3.3
		High + Very high	593.53	130,621	11.64	3.683	13.54

Exposure in 2023 was concentrated mainly along the urban-metropolitan corridor in the western and central sectors of the province. Population density showed intense clusters around the city of Trujillo and its immediately contiguous urban areas, whereas the built-up surface exhibited a similar pattern, although it

extended farther along urban and peri-urban corridors. In contrast, much of the eastern sector showed low values for both variables. This pattern confirms that population and built-up exposure are spatially concentrated in specific areas; therefore, their overlap with zones of moderate to high susceptibility increases the potential for territorial impacts (Fig. 11).

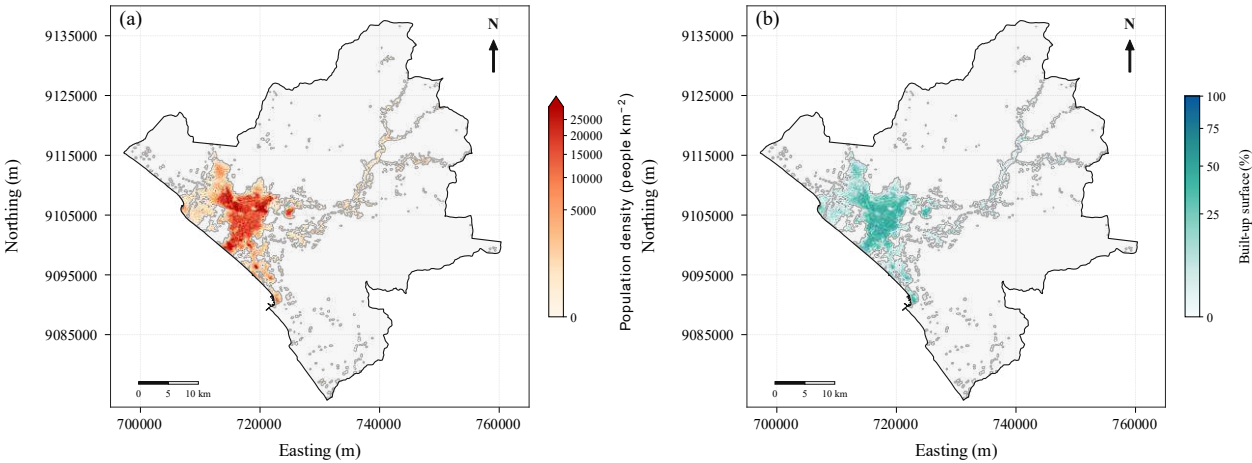


Fig. 11 Spatial distribution of population exposure and built-up surface in the province of Trujillo for the 2023 scenario. (a) population density; (b) percentage of built-up surface

The multitemporal analysis showed that high and very high susceptibility was not completely stable across events, although clearly defined recurrent areas were identified. The overlaps between 2017 and 2023, as well as areas classified as high or very high in all three years, were concentrated mainly in the western and southwestern sectors of the province, suggesting the presence of a persistently susceptible territorial setting. In contrast, classes exclusive to a single year or shared by only two events were more fragmented across central and eastern areas, reflecting the influence of meteorological variability on the spatial response of the model.

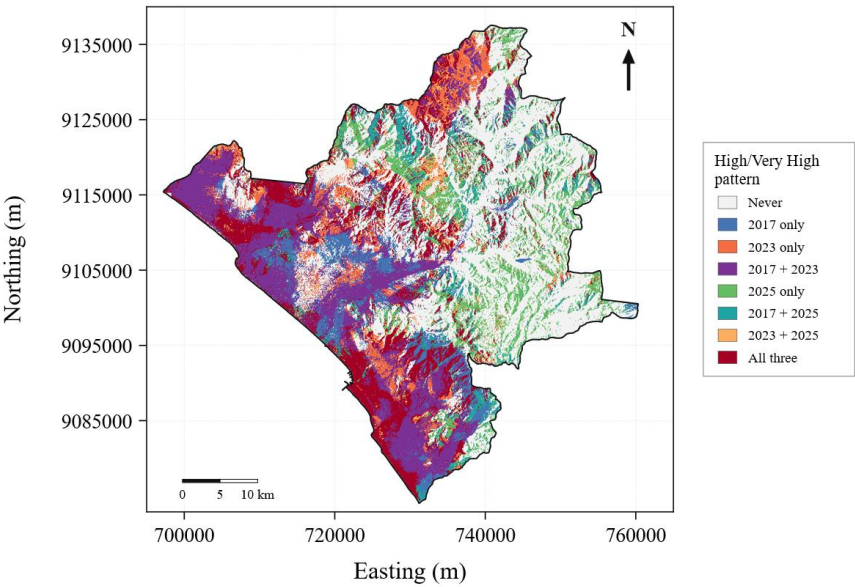


Fig. 12 Spatial persistence of high and very high flood susceptibility classes between 2017, 2023, and 2025

3.6. Dynamic updating of susceptibility and potential exposure

The dynamic update showed a predominance of moderate susceptibility, which covered 1010.02 km², equivalent to 57.17% of the modeled domain. The high and very high classes jointly covered 220.89 km² (12.51%), whereas the low and very low categories represented 30.32% of the territory. Exposure followed a similar pattern: the moderate class concentrated 909,919 people (81.10%) and 21.496 km² of built-up surface (79.02%). In turn, the high and very high classes encompassed 199,726 people (17.81%) and 5.215 km² of built-up surface (19.17%). These results indicate that, under the recent precipitation conditions incorporated into the model, most of the population and built-up surface are currently located in areas of intermediate susceptibility, whereas a smaller proportion is situated in areas of high susceptibility.

Table 7 Spatial distribution of dynamic susceptibility and associated exposure for the scenario updated to 14 September 2026

Susceptibility class	Area (km ²)	Modeled domain (%)	Exposed population (people)	Exposed population (%)	Exposed built-up surface (km ²)	Exposed built-up surface (%)
Very low	32.75	1.85	71	0.01	0.004	0.01
Low	502.96	28.47	12194	1.09	0.489	1.80
Moderate	1010.02	57.17	909919	81.10	21.496	79.02
High	212.11	12.01	199088	17.75	5.199	19.11
Very high	8.78	0.50	638	0.06	0.016	0.06

Figure 13 shows how recent precipitation spatially modifies the model response without the need for retraining. The precipitation accumulated during the 72 h prior to the latest available observation (Fig. 13a) feeds the dynamic meteorological variables and generates a new distribution of susceptibility probabilities (Fig. 13b). The resulting classification (Fig. 13c) shows a predominance of moderate values, with high-susceptibility sectors concentrated mainly toward the western and southwestern parts of the province and localized areas of very high susceptibility. When this response is integrated with population and built-up surface, relative exposure is clearly concentrated in the urban corridor of the western and west-central sector (Fig. 13d). In this way, the approach makes it possible to update susceptibility as precipitation conditions change and to identify where these variations coincide with a greater human and built-up presence.

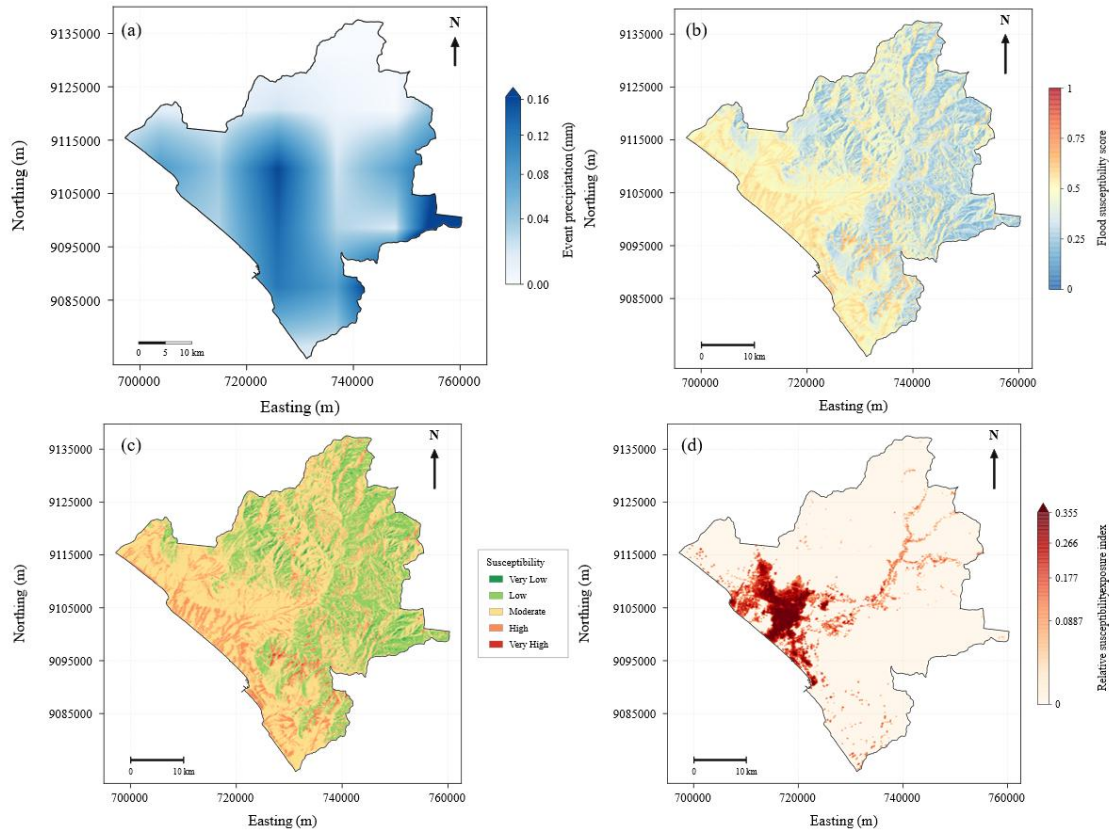


Fig. 13 Dynamic updating of flood susceptibility and associated exposure as of 14 September 2026. (a) recent precipitation derived from GPM-IMERG, corresponding to the 72 h moving window prior to the latest available observation; (b) dynamic susceptibility probability estimated using Random Forest; (c) susceptibility classification into five levels, from very low to very high; and (d) relative exposure index obtained by integrating susceptibility with population and built-up surface

4. Discussion

The patterns obtained show that flood susceptibility in Trujillo responds to a combination of permanent terrain conditions and meteorological factors that vary among events. Random Forest achieved a ROC-AUC of 0.9166 on the test set, close to the 0.920 reported for RF by Li et al. (2026) and consistent with the strong performance of tree-based models reported by Demissie et al. (2024) and Badillo-Rivera et al. (2025). More important than the differences among algorithms is the fact that the areas of highest susceptibility were recurrently concentrated in low-lying sectors, relief-transition zones, and drainage-associated corridors, a pattern similar to that observed in other regions where elevation, slope, proximity to drainage channels, and precipitation control a large part of the spatial distribution of flooding. In Trujillo, the persistence of high and very high susceptibility areas across 2017, 2023, and 2025 suggests the existence of a relatively stable territorial predisposition upon which the specific rainfall conditions of each event act.

The SHAP interpretation reinforces this finding, as terrain aspect, precipitation components, elevation, and slope were among the factors with the greatest contributions. This result partially agrees with Badillo-Rivera et al. (2025), who found an important contribution of aspect and geomorphological variables in Piura, and with Li et al. (2026), where elevation, maximum 24 h precipitation, distance to rivers, and slope were the main controls. Differences in the ranking of variable importance should not be regarded as

contradictory, since susceptibility depends on the physical configuration of each basin and on the characteristics of the event used to construct the inventory. In this case, the presence of all three precipitation components among the most influential variables is particularly relevant because it shows that the same topographic configuration may respond differently under different rainfall durations and intensities.

From a territorial perspective, identifying susceptible areas becomes more important when they overlap with densely populated and built-up areas. In 2017, the high and very high classes accounted for 52.95% of the population and 56.42% of the evaluated built-up surface, whereas these proportions were considerably lower in 2025. This variation shows that the spatial extent of a susceptible area does not by itself determine the potential magnitude of its consequences; its location relative to human settlements is also important. This idea is consistent with Ehrlich et al. (2018), who highlight that population and built-up surfaces make it possible to spatially represent exposure, and with Tellman et al. (2021), who found that the population living in areas where floods were observed increased by 20–24% globally between 2000 and 2015. In urban contexts, this overlap may translate into impacts on housing, roads, services, and infrastructure; moreover, exposure may have more severe social consequences when it coincides with populations with a lower capacity to respond and recover, as also noted by Rentschler et al. (2022).

The dynamic component broadens the usefulness of the model by preventing susceptibility from being represented by a single permanent map. By incorporating recent GPM-IMERG precipitation, the spatial response can be updated while keeping the physical factors of the territory constant, in agreement with Mosaffa and Brocca (2024), who propose that susceptibility may vary as meteorological conditions change. In the scenario updated to 14 September 2026, the moderate class predominated, covering 57.17% of the modeled domain and accounting for 81.10% of the population and 79.02% of the built-up surface. In contrast, the high and very high classes jointly represented only 12.51% of the territory, but overlapped with 17.81% of the population and 19.17% of the built-up surface, showing that even a relatively smaller spatial extent may be relevant when it intersects occupied areas. These values do not represent the extent that will necessarily be flooded, but rather susceptibility conditioned by the available precipitation.

Table 8 Comparison of the main results with recent studies on flood susceptibility

Study	Area / approach	Main result	Relationship with the present study
Present study	Trujillo, Peru; RF, XGBoost, SVM, and ANN-MLP; Sentinel-1, IMERG, and GHSL	RF ROC-AUC = 0.9166	Integrates multi-event susceptibility, exposure, and dynamic updating
Badillo-Rivera et al. (2025)	Piura, Peru; Sentinel-1 + ML	RF and variants outperformed SVM; validation AUC > 0.80	Consistent with the performance of RF and the relevance of relief/aspect
Demissie et al. (2024)	USA; six ML models	RF and XGBoost: accuracy of 0.82–0.97	Confirms the usefulness of tree-based models with topographic and hydrological variables

Li et al. (2026)	China; RF, XGBoost, SVM, and MLP	XGBoost = 0.938; RF = 0.920	Results close to those obtained in Trujillo and predominance of tree-based models
Tellman et al. (2021)	Global flood assessment	Population exposure increased by 20–24%	Supports the relevance of integrating susceptibility and population
Mosaffa and Brocca (2024)	Mediterranean region; dynamic RF	Susceptibility varies with precipitation and temporal conditions	Consistent with the proposed meteorological updating approach

5. Conclusions

The multi-event approach made it possible to represent flood susceptibility in Trujillo by integrating the observed flood footprints from 2017, 2023, and 2025 with topographic, hydrological, geological, and meteorological variables. Random Forest showed the most consistent performance, with a ROC-AUC of 0.9166, AP of 0.9116, accuracy of 0.8371, and F1-score of 0.8393 on the independent test set, slightly outperforming XGBoost and showing a larger difference compared with ANN-MLP and SVM. The SHAP analysis showed that terrain aspect, precipitation components, elevation, and slope were the factors with the greatest contribution, demonstrating that susceptibility depends on the interaction between the physical predisposition of the territory and the meteorological conditions of each event.

Integration with GHSL showed that exposure depends on the spatial overlap among susceptibility, population, and built-up surface. In 2017, the high and very high classes accounted for 52.95% of the population and 56.42% of the built-up surface, whereas in 2025 these proportions decreased to 11.64% and 13.54%, respectively. The dynamic component made it possible to update susceptibility using recent GPM-IMERG precipitation without retraining the model. For the 14 September 2026 scenario, the moderate class predominated, accounting for 57.17% of the modeled domain, 81.10% of the population, and 79.02% of the built-up surface. In contrast, the high and very high classes jointly represented 12.51% of the territory but accounted for 17.81% of the population and 19.17% of the built-up surface.

The main limitations are related to the use of a random train–test partition, which does not constitute independent spatial validation, the native meteorological resolution of IMERG, and the modeled nature of GHSL for 2025. Therefore, the results should be interpreted as estimates of susceptibility and potential exposure rather than as a hydraulic simulation of the actual extent of flooding. Future work should validate the model using new independent events, assess its spatial and temporal transferability, compare dynamic updates against newly observed flood footprints, and incorporate higher-resolution hydrometeorological information. These improvements would strengthen its application as a decision-support tool for monitoring, territorial planning, and preventive flood-risk management.

Statements and Declarations

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

Marco A. Cotrina-Teatino, Jairo J. Marquina-Araujo, and José N. Mamani-Quispe contributed to the conception and design of the study, interpretation of the results, and preparation of the manuscript. All authors reviewed and approved the final version of the manuscript.

Data Availability

The datasets used in this study were derived from publicly available remote-sensing, meteorological, geospatial, and population datasets described in the Materials and Methods section. The processed datasets and derived products supporting the findings of this study are available from the corresponding author upon reasonable request.

Ethics Approval

Not applicable. This study did not involve human participants, animals, or personally identifiable data.

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Appendix

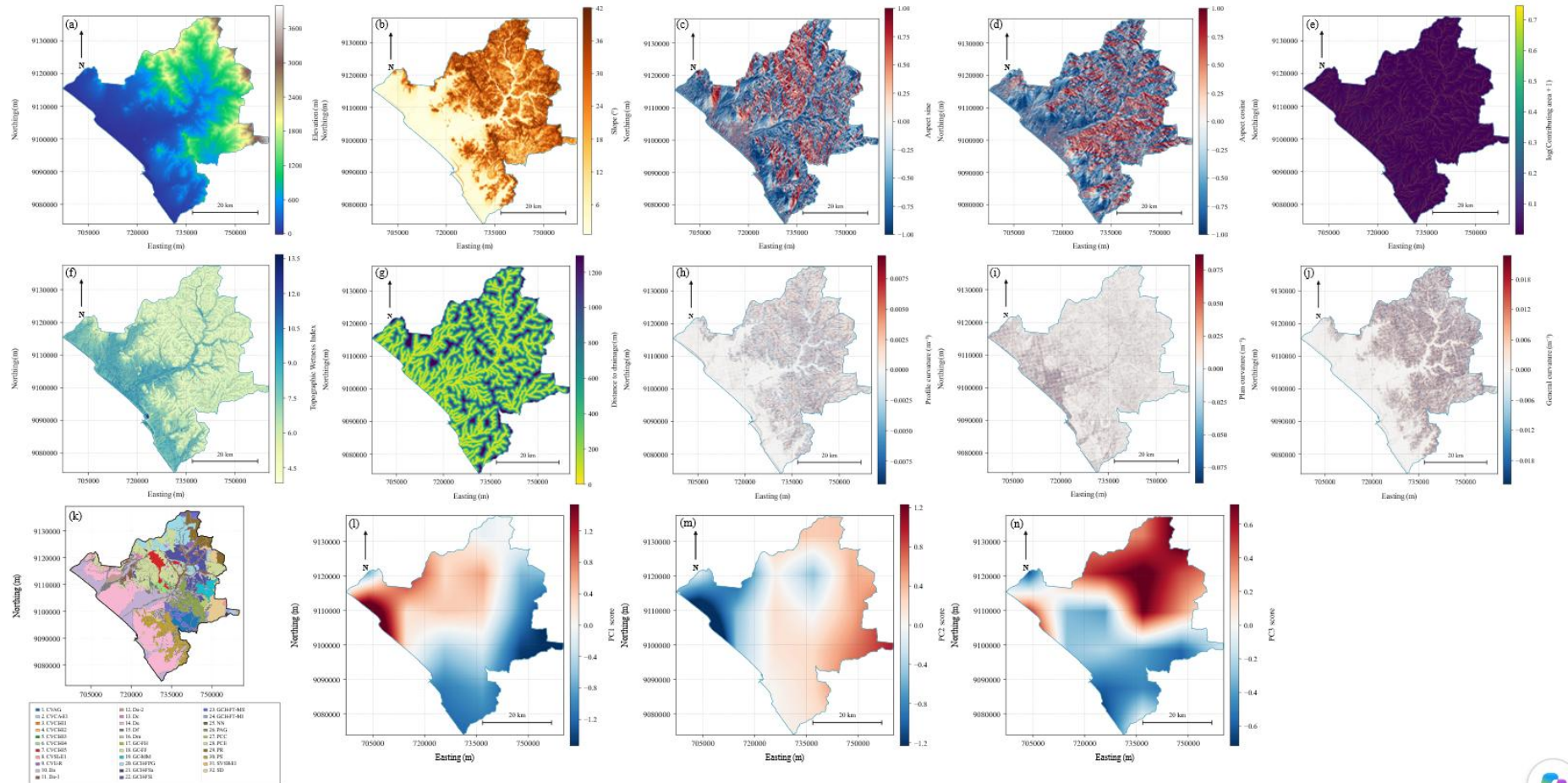


Fig. 14 Topographic, hydrological, geomorphometric, geological, and meteorological variables used in the geospatial modeling. (a) Elevation; (b) slope; (c) aspect, sine component; (d) aspect, cosine component; (e) transformed contributing area; (f) topographic wetness index; (g) distance to drainage; (h) profile curvature; (i) plan curvature; (j) general curvature; (k) geological units; (l) precipitation PC1; (m) precipitation PC2; and (n) precipitation PC3

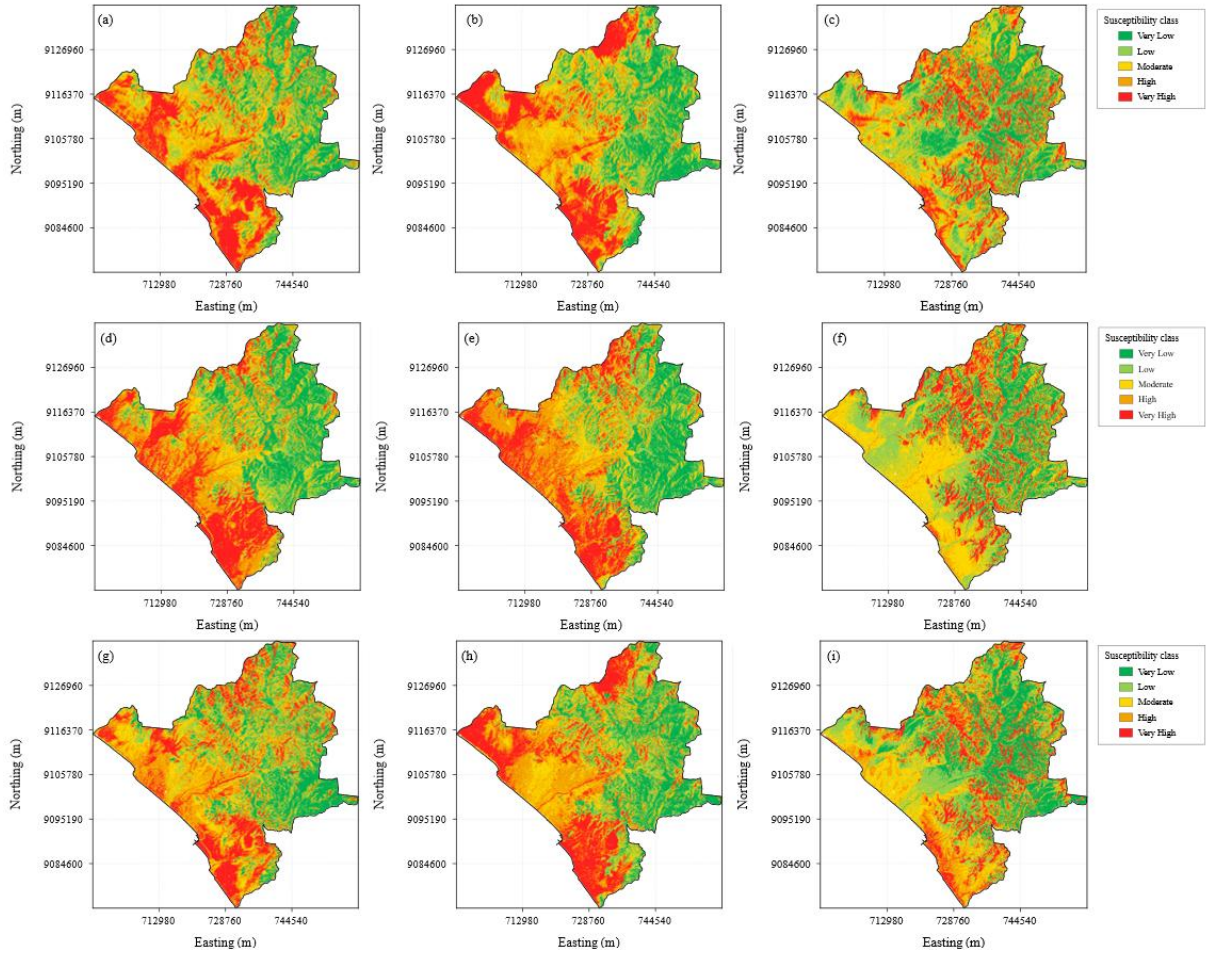


Fig. 15 Temporal predictions of flood susceptibility classification. (a) XGBoost 2017; (b) XGBoost 2023; (c) XGBoost 2025; (d) SVM 2017; (e) SVM 2023; (f) SVM 2025; (g) ANN-MLP 2017; (h) ANN-MLP 2023; and (i) ANN-MLP 2025